Application of CNNs for Brain MRI Image Segmentation

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INTRODUCTION

Semantic segmentation of brain tumors based on magnetic resonance imaging (MRI) is a crucial step in determining their type and location, as well as in contributing to a more accurate diagnosis for a patient.

Gliomas, a type of primary brain tumor, are differentiated into low-grade gliomas (LGG) and high-grade gliomas (HGG), depending on their aggressiveness. Glioma sub-regions include the whole tumor, its core, enhancing tumor and necrotic structures (see Figure 1).

MRI IMAGES

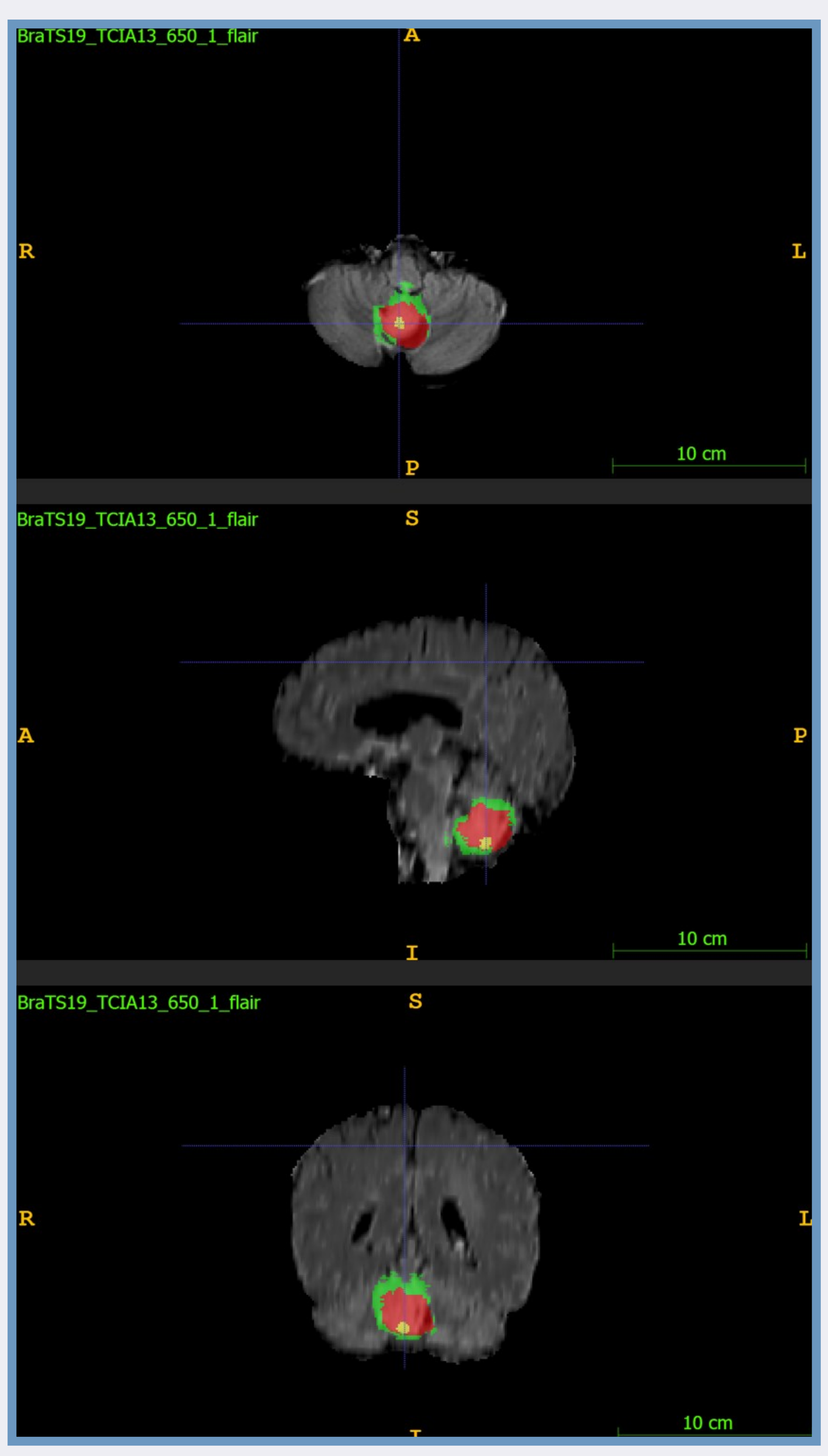

Figure 1. Glioma sub-regions in axial, sagittal and coronal planes, visualized in ITK-SNAP [1]. BraTS19 [2] data.

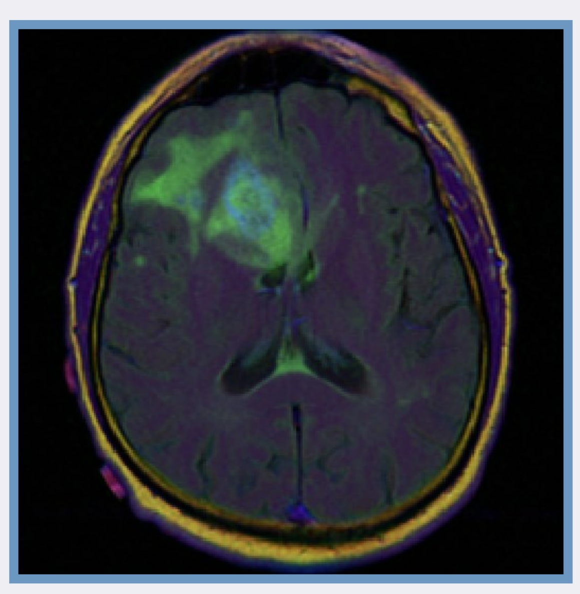

Figure 2. LGG in the axial plane.

Figure 3. Abnormality segmentation mask, 256 x 256.

- The dataset is composed of 110 patients' pre-operative FLAIR scans. Images were collected [3] from The Cancer Imaging Archive. They were also preprocessed and augmented [4].
- MRI scans are from 5 medical centers.
- Abnormality segmentation masks are presented in the axial plane (see Figures 2 and 3).

SEGMENTATION RESULTS

Architecture	Dice similarity coefficient
U-Net [4]	0.870
Attention U-Net [5]	0.877
SegNet	0.800

INTERPRETABILITY

Interpretable models allow us to build trust in the system, especially in high-impact areas. Medical experts can assess if a given explanation corresponds to relevant diagnostic criteria. Model-agnostic post hoc explainability methods can be integrated with CNN models.

Grad-CAM allows to visualize class activation maps. Gradients of the relevant class, reaching the last convolutional layer, help to visualize explanations. Warmer colors correspond to areas that are more important in the model's decision. As can be expected, when applying Grad-CAM on models that were pretrained on images from non-medical domains, we do not get good explanations that could be related to diagnostic criteria (see Figure 4).

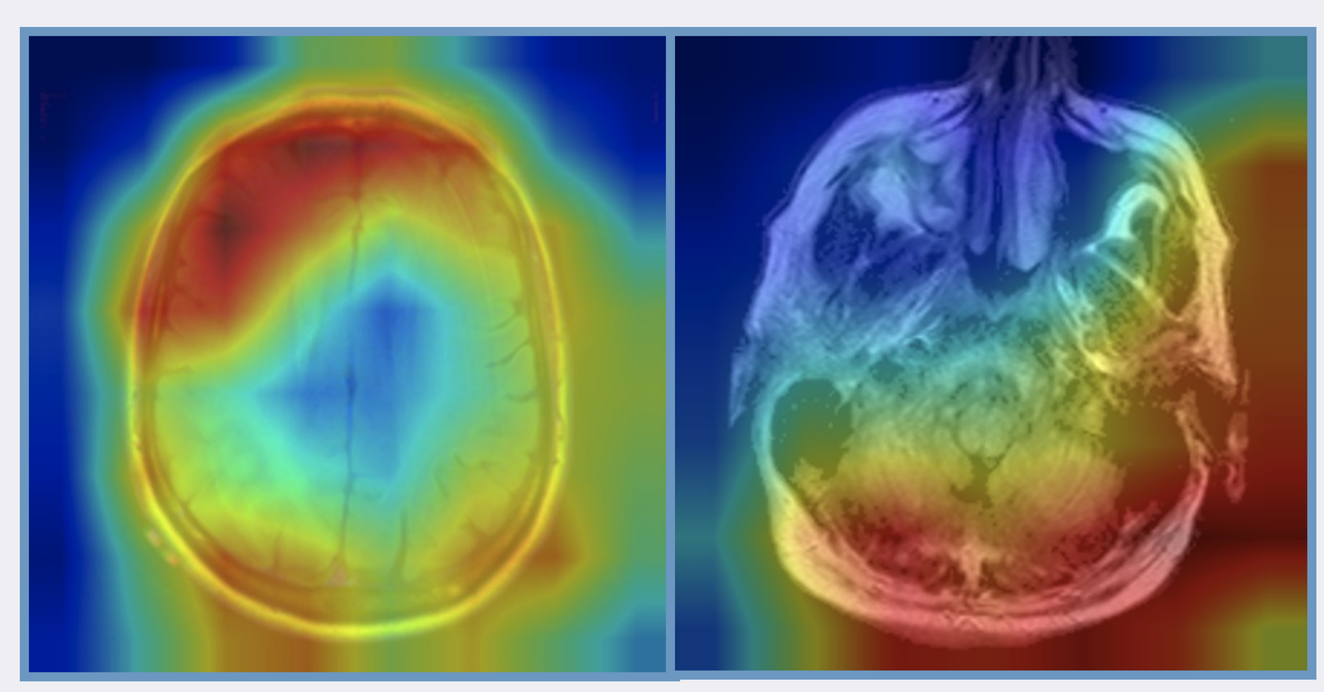

Figure 4. Application of Grad-CAM [6].

CONCLUSION

After testing three 2D encoder-decoder networks we observed the following:

- Attention U-Net achieved the best result in terms of Dice coefficient (0.877).
- The Grad-CAM explainability method could serve as an additional tool for experts to check if a good Dice score corresponds to the appropriate diagnostic criteria.

References: **[1]** Yushkevich et al. User-guided 3D active contour segmentation of anatomical structures: Significantly improved efficiency and reliability. *Neuroimage*. 2006. **[2]** Menze et al. The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS). IEEE Transactions on Medical Imaging. 2015. **[3]** Buda M. LGG Segmentation Dataset. 2017. kaggle.com/mateuszbuda/lgg-mri-segmentation **[4]** Buda M. and contributors. U-Net implementation in PyTorch for FLAIR abnormality segmentation in brain MRI. 2019. github.com/mateuszbuda/brain-segmentation-pytorch **[5]** Lee J. H. Pytorch implementation of U-Net, R2U-Net, Attention U-Net, Attention R2U-Net. 2017. github.com/LeeJunHyun/Image_Segmentation **[6]** Gildenblat J. and contibutors. PyTorch library for CAM methods. 2021. github.com/jacobgil/pytorch-grad-cam